Regional Climate Forecasting Via Statistical Downscaling as well as by Pure Statistics

Alexander Gershunov

Climate Research Division

Scripps Institution of Oceanography

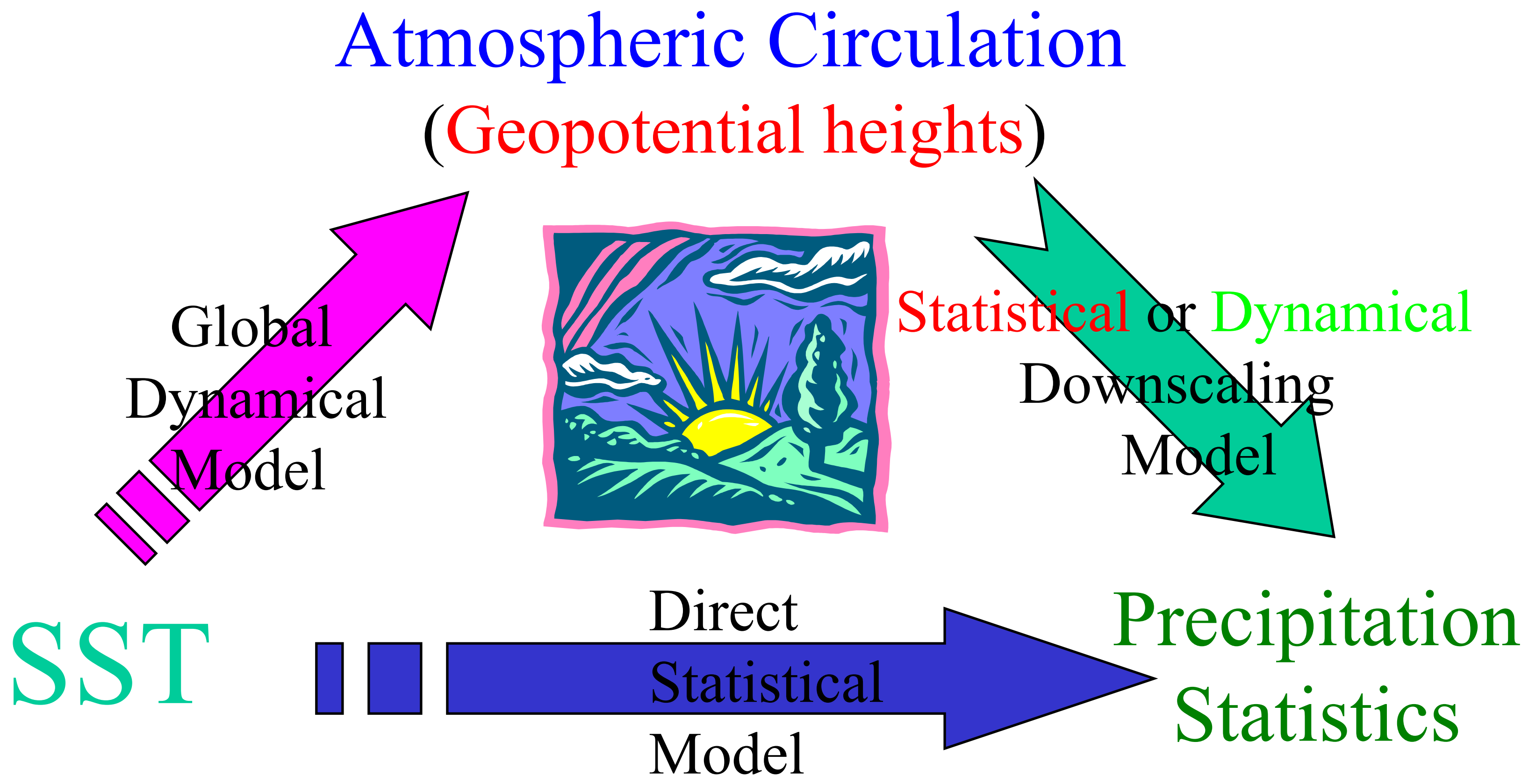
Aim: Predictability and projection of weather statistics with useful resolution and skill

- Overview of relevant methods
- Comparison of seasonal forecast skill achieved with statistical, hybrid (statistical downscaling of GCM) and fully dynamical techniques
  - Winter (JFM) 1998 California precipitation
- Statistical and hybrid predictability of precipitation with and without ENSO forcing
  - JFM heavy daily precip in the contiguous United States
  - Seasonal cycle of skill for various precip variables
- Hybrid projections of anthropogenic climate change

Three Forecasting Methods

- Statistical approach
  - » Observed predictor and predictand fields are statistically related to each other at lags
- Hybrid approach (dynamical/statistical)
  - » global model forecast downscaled to regional precipitation using statistical relationship with station observations
- Fully dynamical approach
  - » Climate model forecast downscaled to regional precipitation using nested dynamical regional models

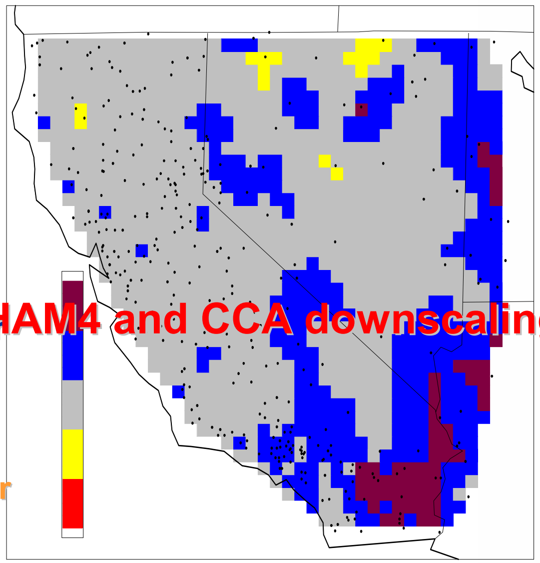
Dynamical, Hybrid and Statistical Forecasting Approaches



JFM 1998

Total Precipitation via a CCA-based statistical model

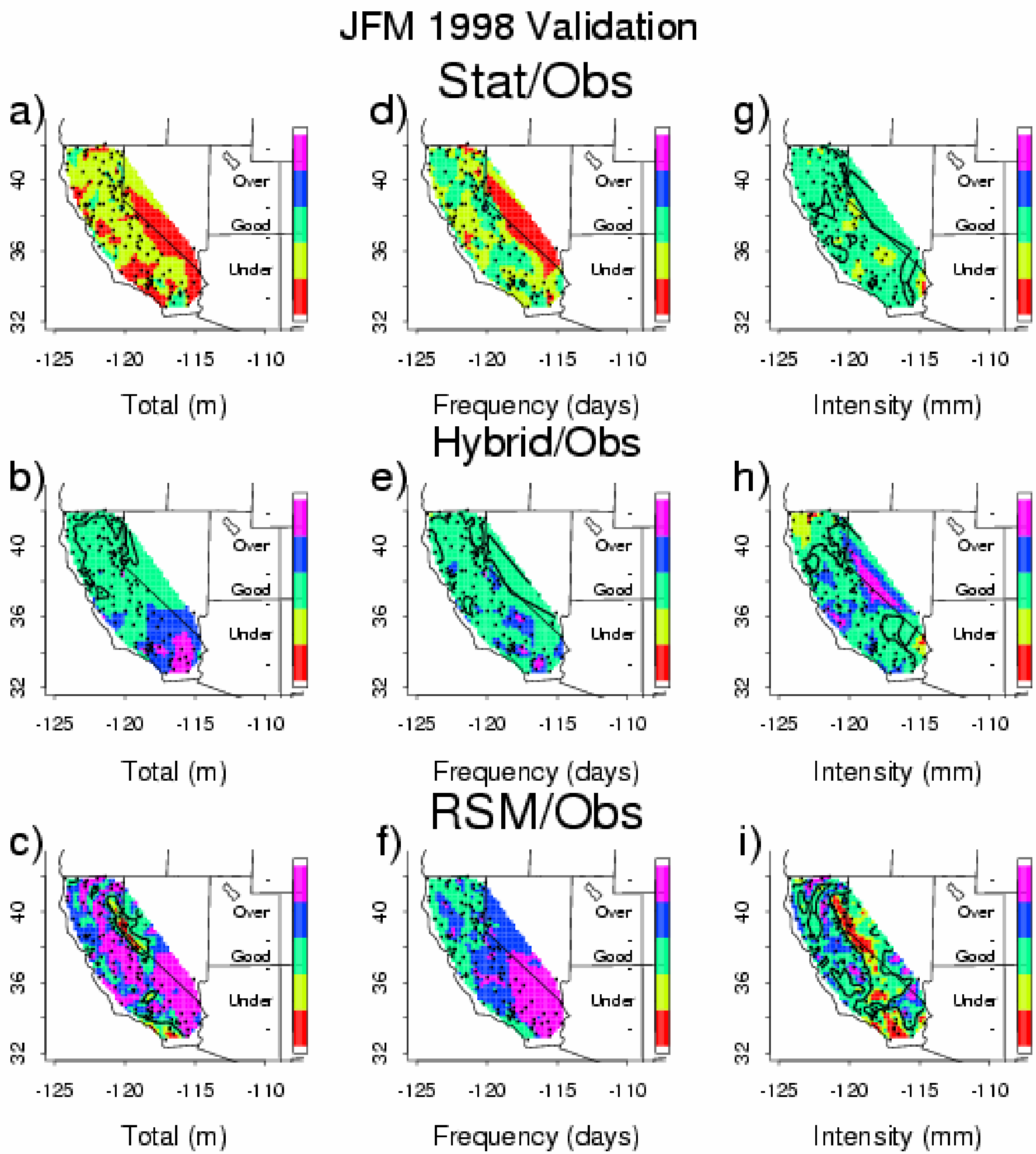
ENSO composite model



ECHAM4 and CCA downscaling

ECHAM4 and RSM downscaling

How about forecasting frequency of extreme daily precipitation?



Gershunov et al., 2000, Journal of Hydrometeorology

Data

Predictands

Daily station precipitation data (Eischeid et al. 2000) at 262 stations (points on Figures 2 and 6) 1950 1999.

A “heavy” precipitation event is defined as daily precipitation total above the 90^{th} percentile of the seasonal local (station) 50-year (1950-1999) climatology. Seasonal frequency of such events (P90) is the main variable considered here.

Total seasonal precipitation (Ptot) and frequency of daily precipitation total above the 50^{th} and 75^{th} percentiles (P50 and P75 respectively) are also considered.

Predictors

SST data (Reynolds and Smith 1994) cover the common time period 1950-1999. They are the same data used to force the AGCMs used here.

Atmospheric circulation fields used as predictors are 500mb heights from NCEP/NCAR ReanalysisI (Kalnay et al. 1996) and from the ECHAM3 and CCM3 AGCMs, all for the common period 1950-1999 and from the NSIPP AGCM for the period 1961-1999. All AGCM data are 10-member ensemble averages resolved on the T42 grid (roughly 2.8° x 2.8°).

Hybrid Methodology

- **Predictor:** Large-scale atmospheric circulation (i.e. 500mb heights) from 50-year global SST-forced AGCM ensemble integration
- **Predictand:** Monthly precipitation or any statistic of observed weather/hydrology
- **Statistical model:**
  - » Predictor and Predictand fields are pre-filtered with p Principal Components (PCs)
  - » Patterns of variability in the Predictor and Predictand fields represented by their p respective PCs are related to each other via k canonical correlates derived from Canonical Correlation Analysis (CCA). $k \leq p \ll T$, where T is the number of temporal observations available for model training
  - » The optimal statistical model is defined by considering cross-validated measures of skill for all reasonable combinations of p and k displayed on the Skill Optimization Surface (SOS)
- **Forecast:** Global SST is operationally forecast. The AGCM is forced by forecast SST. The Predictor field (500mb heights) is computed. Patterns in dynamically predicted circulation are downscaled to the Predictand using the optimal statistical model.

Statistical Methodology

•**Predictor:** Observed monthly SST over a relevant geographic area

•**Predictand:** Observed monthly precipitation (lagging the SST field)

•**Statistical model:**

»Predictor and Predictand fields are pre-filtered with p Principal Components (PCs)

»Patterns of variability in the Predictor and Predictand fields represented by their p respective PCs are related to each other via k canonical correlates derived from Canonical Correlation Analysis (CCA). $k \leq p \ll T$, where T is the number of temporal observations available for model training

»The optimal statistical model is defined by considering cross-validated measures of skill for all reasonable combinations of p and k displayed on the Skill Optimization Surface (SOS)

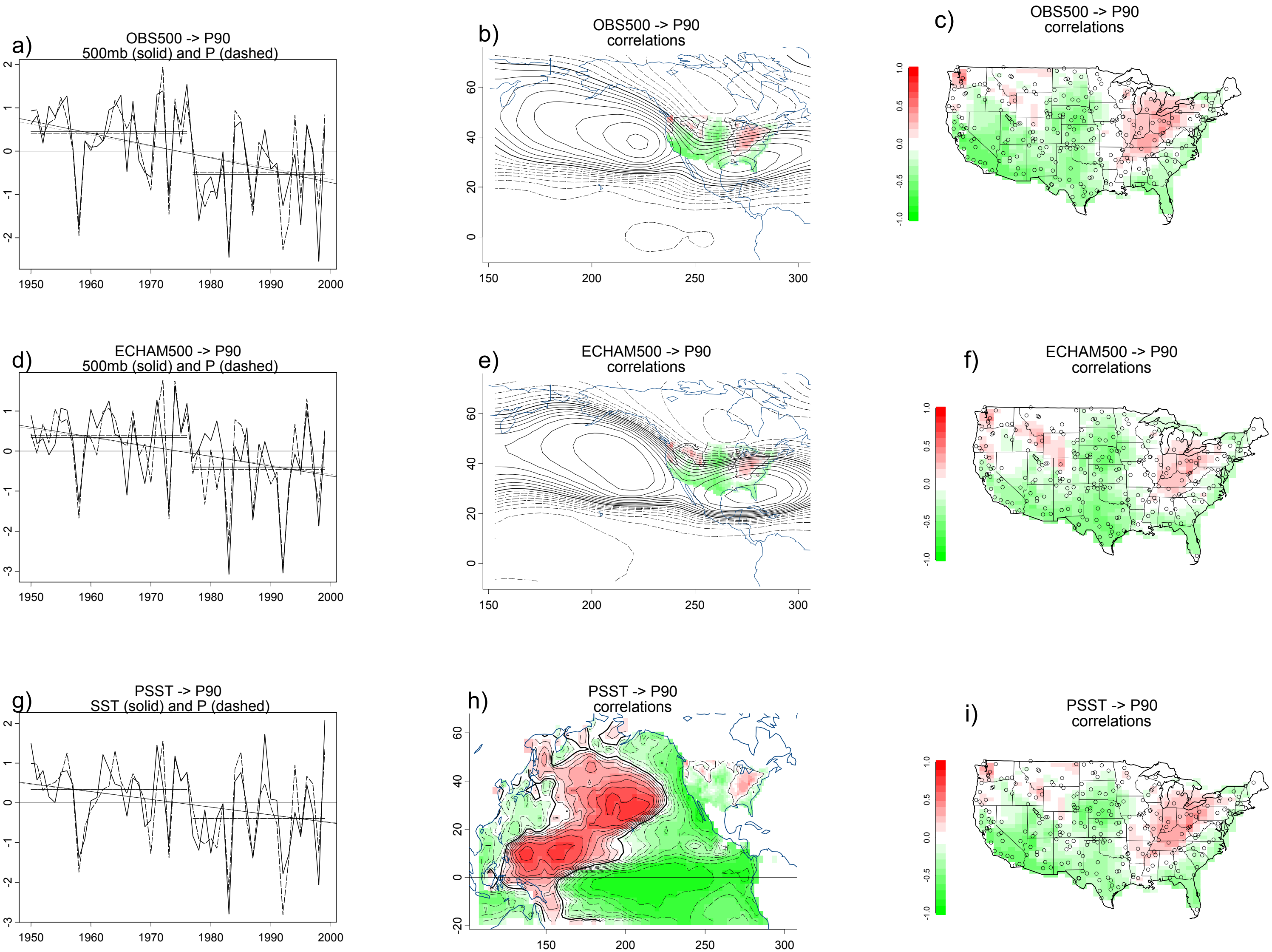
•**Forecast:** Patterns in the SST field observed at appropriate lead time are downscaled to the Predictand using the optimal statistical model.

Leading Coupled Mode: various predictors

Observed 500mb

Modeled 500mb

Observed Pacific SST



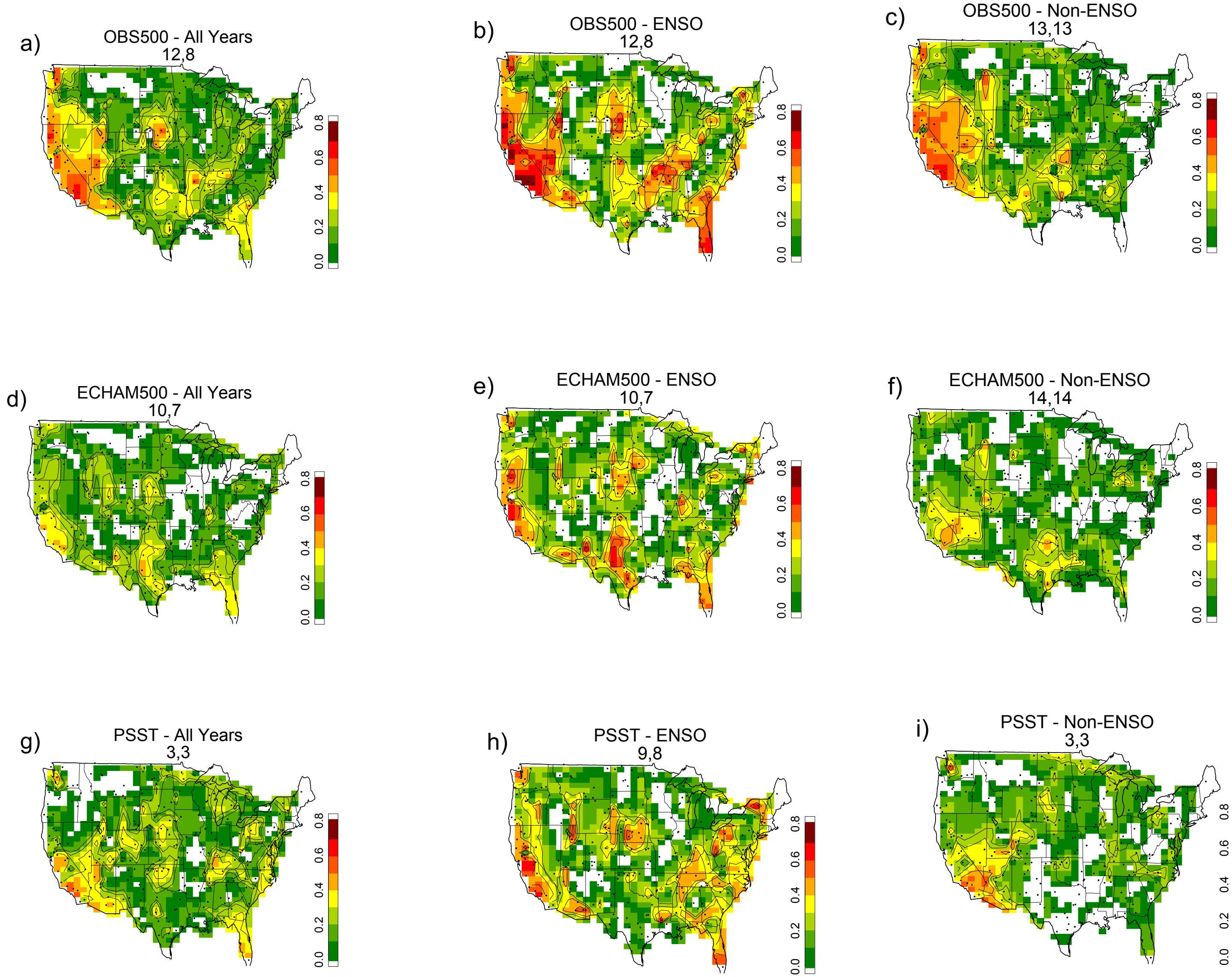
Gershunov and Cayan, 2003, Journal of Climate

Specification Skill: JFM P90

Observed 500mb

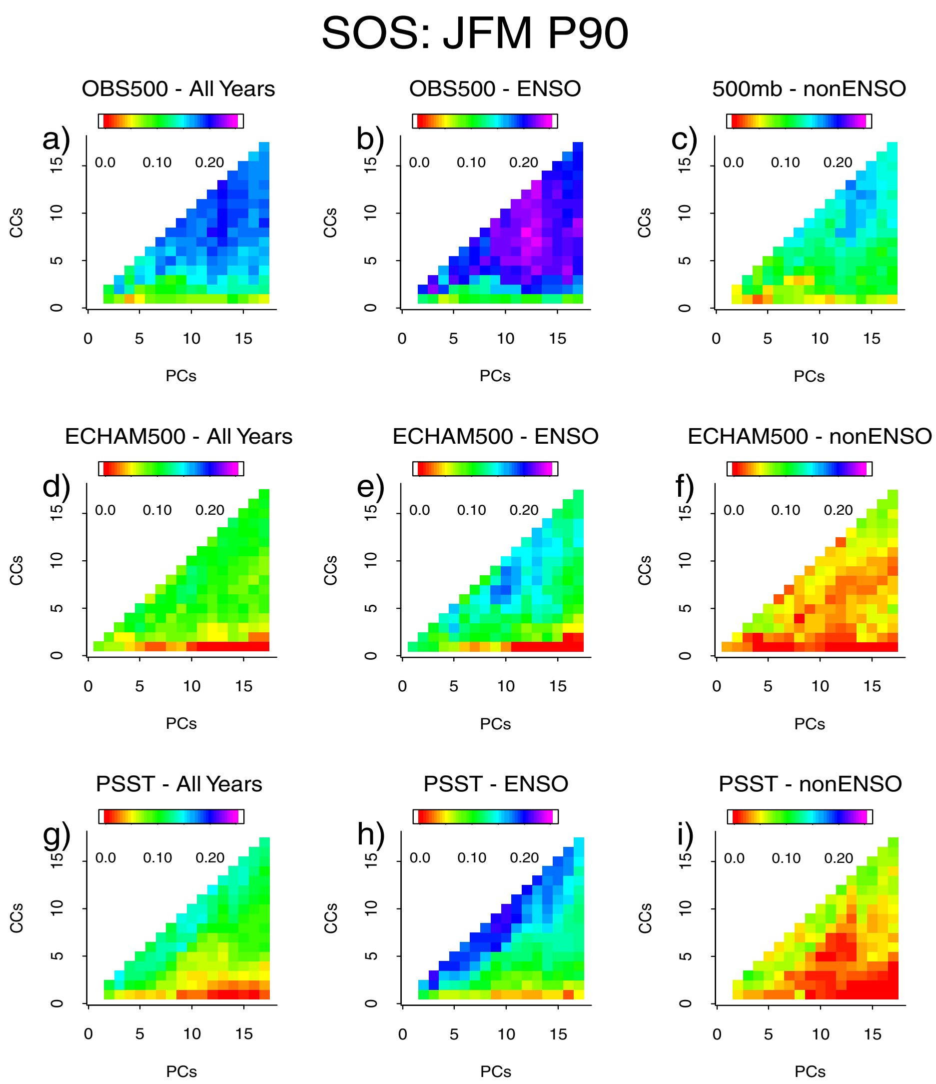
Modeled 500mb

Observed Pacific SST



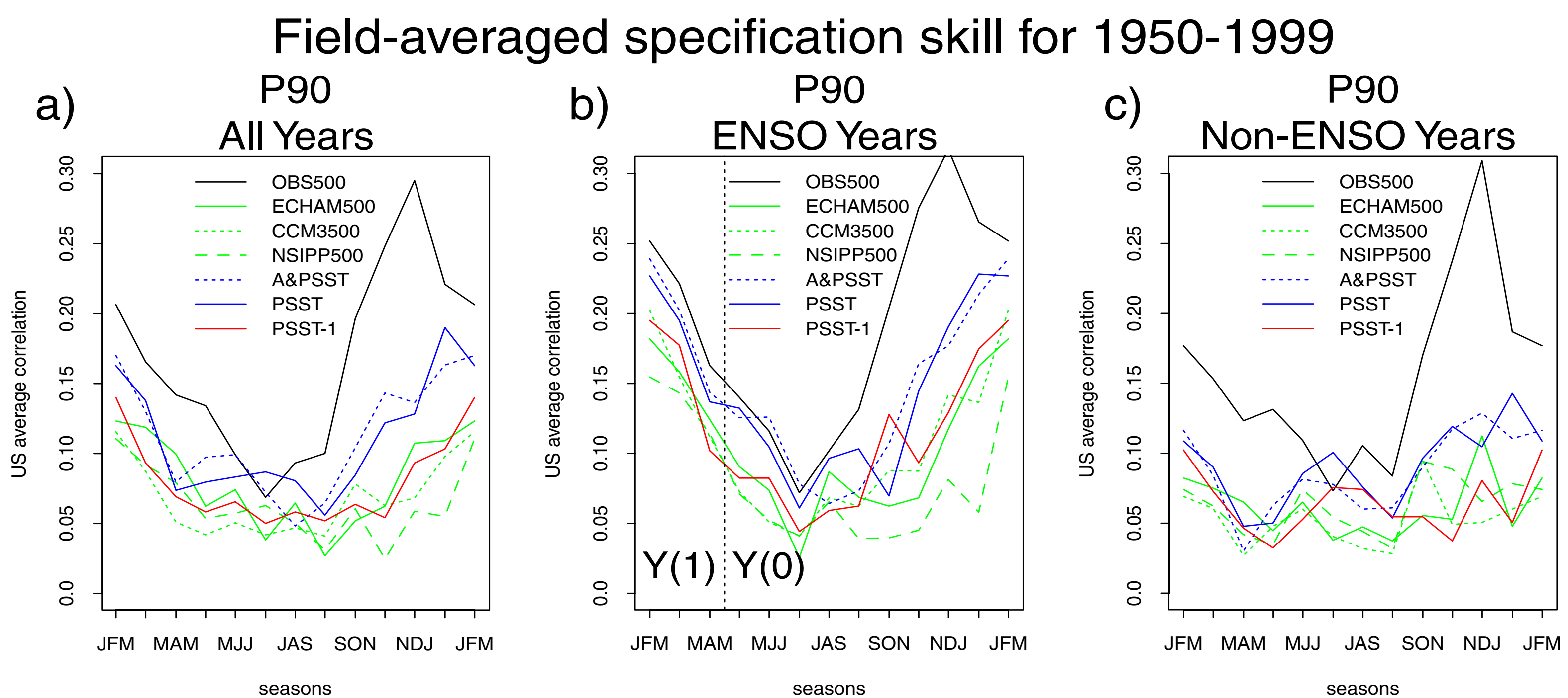
Gershunov and Cayan, 2003, Journal of Climate

Skill Optimization Surface



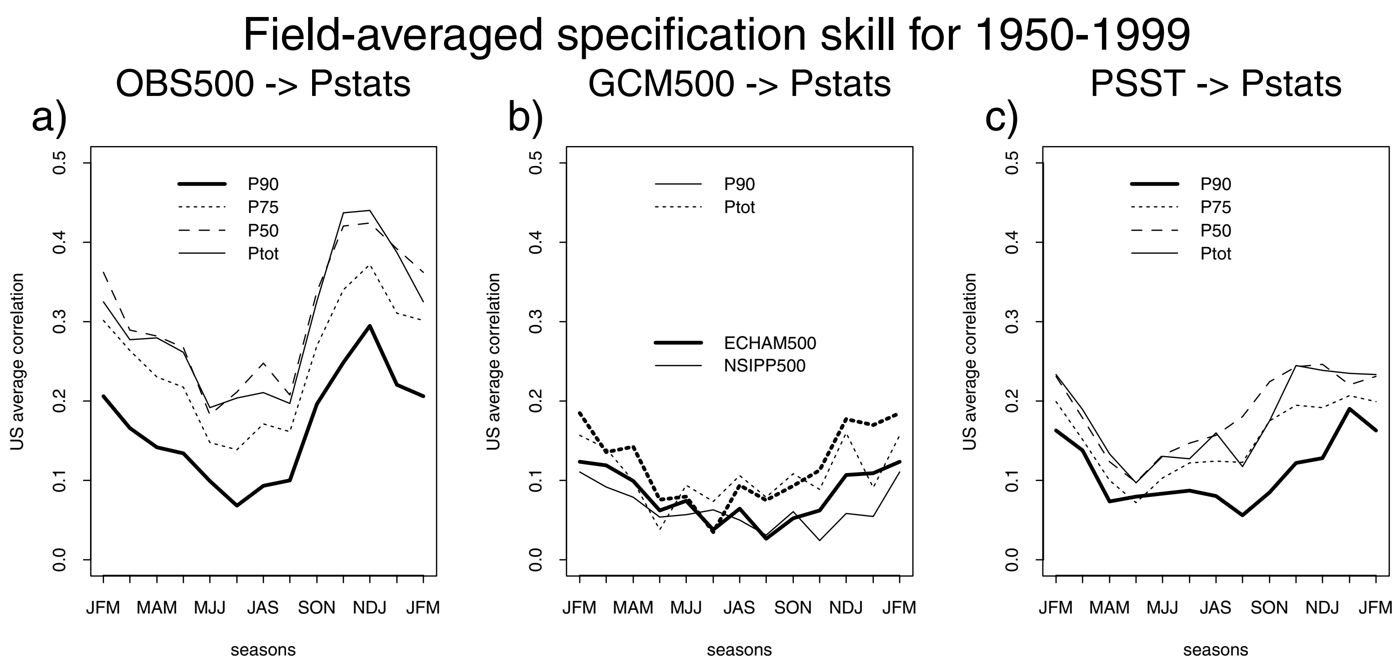
Gershunov and Cayan, 2003, Journal of Climate

Field-Averaged Specification and Prediction Skill



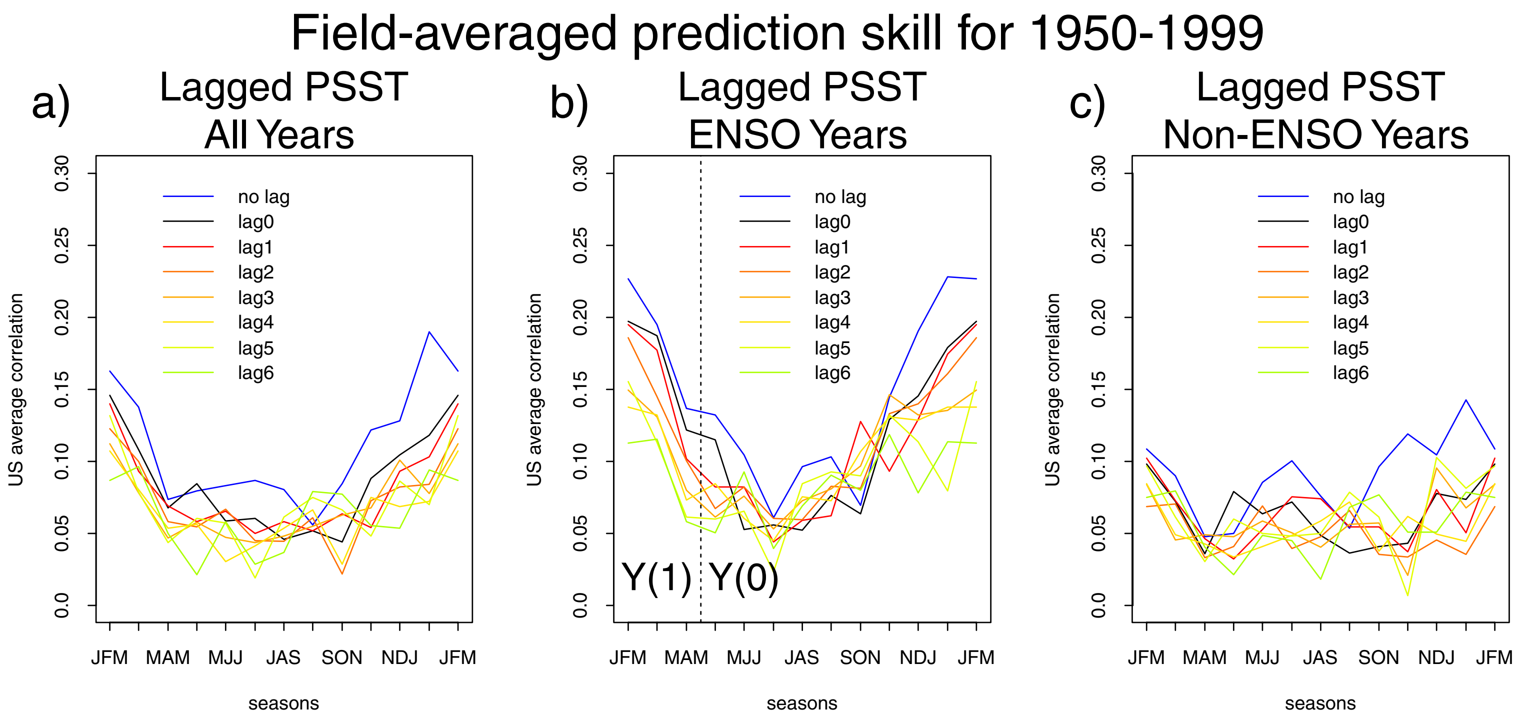
Gershunov and Cayan, 2003, Journal of Climate

Field-Averaged Specification Skill For Other Precipitation Variables



Gershunov and Cayan, 2003, Journal of Climate

Field-Averaged Statistical Prediction Skill



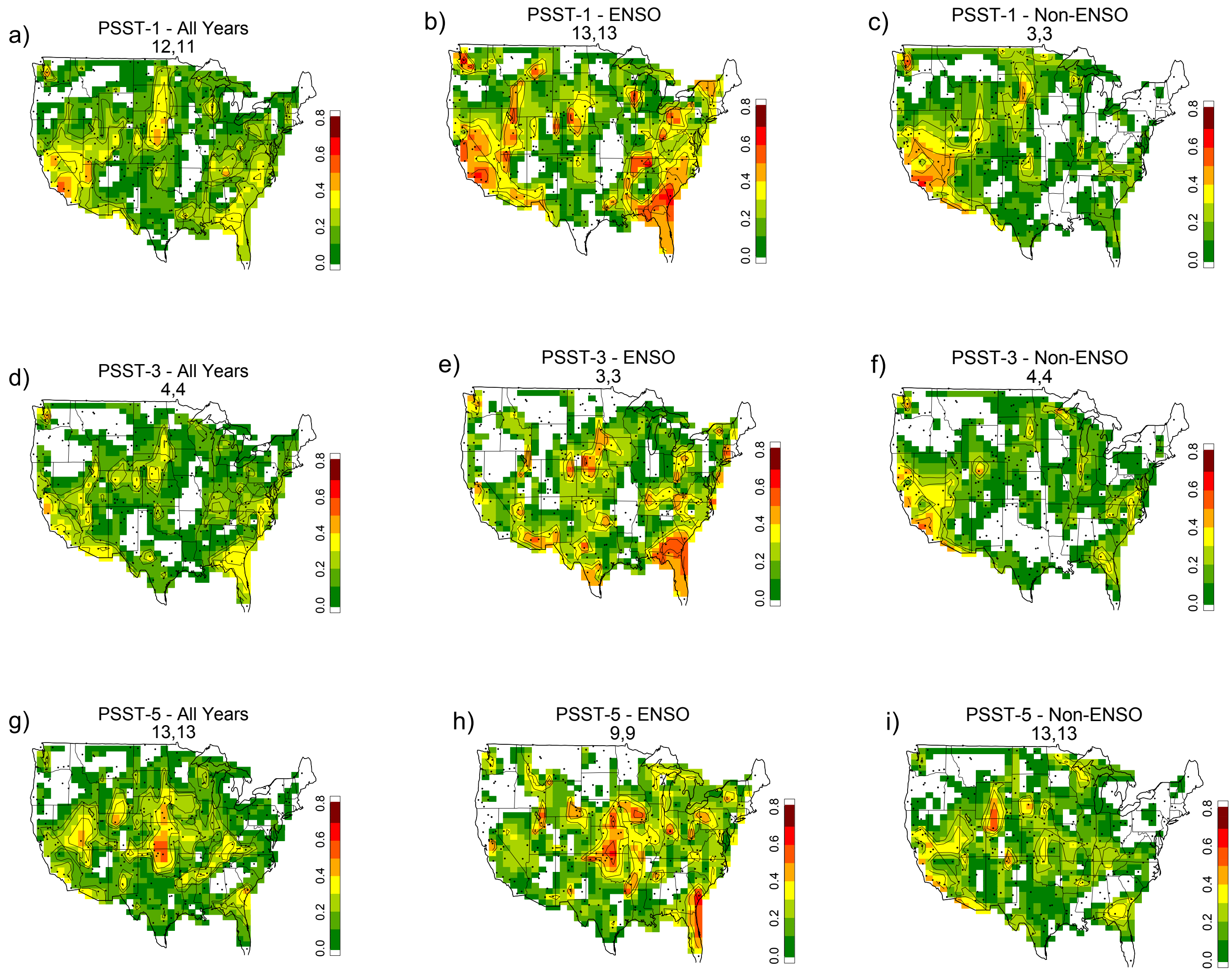
Gershunov and Cayan, 2003, Journal of Climate

Statistical Prediction Skill: JFM P90

December Pacific SST

October Pacific SST

August Pacific SST

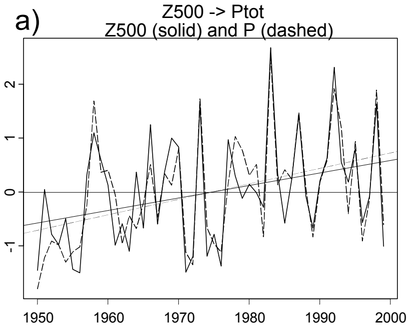


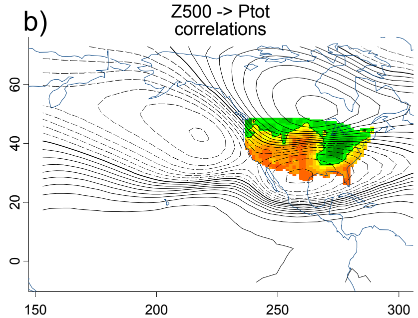
Gershunov and Cayan, 2003, Journal of Climate

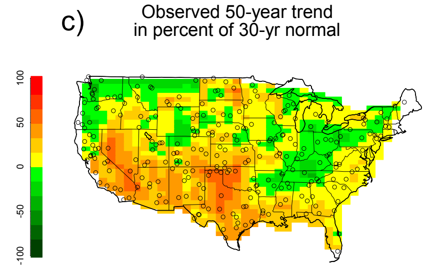
Hybrid vs. Statistical Summary

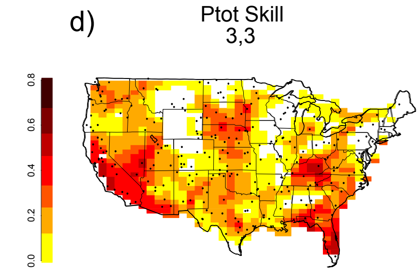
- Seasonal frequencies of heavy daily precipitation are predictable via statistical and hybrid methods
- Less extreme statistics can be better predicted by either method
- Skillful seasonal predictability is achieved for ENSO as well as for non-ENSO years
- Pure statistical methodology is preferable for seasonal prediction
- Hybrid methods can be used for regional projections of long-term climate change

Anthropogenic climate change projections for 2001 – 2030 via statistical downscaling

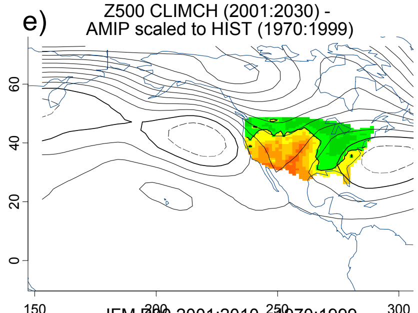


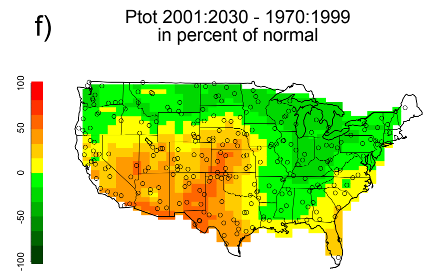


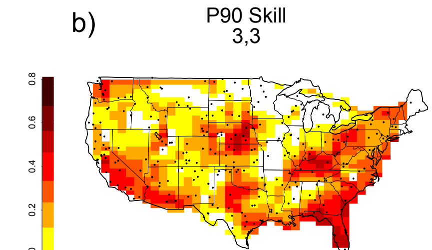




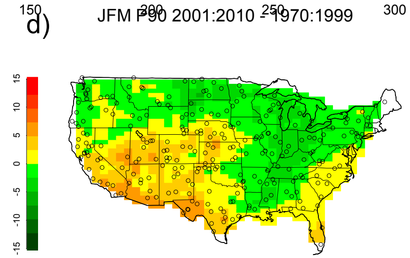
JFM total precipitation (Ptot). Leading mode of co-variability and trend of atmospheric circulation (500mb heights, Z500) from an AMIP run of the CCM3 (the atmospheric component of the PCM forced with observed global SST) and Ptot (a). The leading coupled pattern of Z500 and the observed Ptot (b) expressed as correlations between the data and the time series in (a). Contours are drawn at 0.1 intervals, negative contours are dashed. The observed Ptot trend expressed in percent of normal local precipitation for the 1971-1999 period (c). The skill of the statistical model in explaining the observed Ptot trend from the modeled-simulated Z500 signal expressed as correlation at each location (d). The projected climate change pattern in Z500 (e) and the Ptot change pattern predicted from it (e and f), both expressed in difference between the projected 30-yr 2001-2030 and 1970-1999 periods (contours on plate e are drawn every 5 meters, negative contours are dashed). Plates (g, h and i) show the progression of Ptot change by decade.

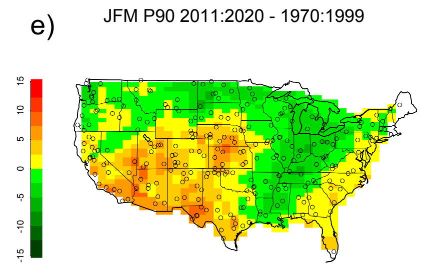


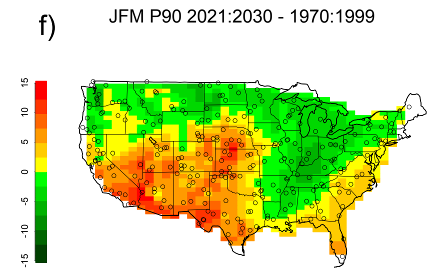


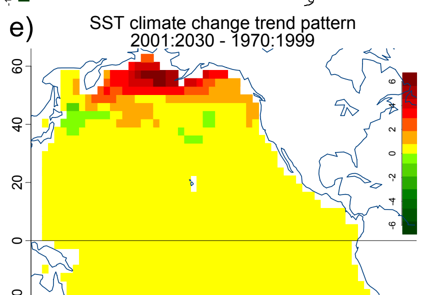


Projected P90 trend by decade

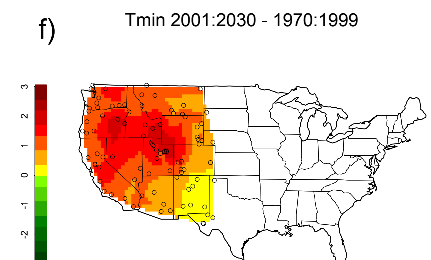








And temperature trend associated with SST trend



Seasonal - Interannual Prediction

We know how to do this

- Dynamical downscaling may dominate in the future, but for now, it is the brute force solution
- Statistical downscaling is the compromise solution
- Statistical prediction (implicitly downscaled) is the reasonable solution

Climate Change Prediction

We don't yet know how to rigorously evaluate skill

- Dynamical downscaling: the brute force solution
- Statistical downscaling: the creative solution

Statistical vs. Dynamical Downscaling

Disadvantages of Statistical Downscaling:

» Requires observational data

» Assumes stationarity of relationships

» Does not predict more than a few variables at a time (no explicit guarantee of dynamical consistency)

Advantages of Statistical Downscaling:

» Seasonal forecasting skill can be assessed rigorously and simply

» Acts as an implicit GCM bias corrector

» Can be used in diagnostic as well as in prognostic modes

» Can use large-scale patterns rather than regional grid cells for inputs

» Provides a reasonable alternative to dynamical downscaling of global climate change simulations in well-observed regions

» Built-in reality control

Where do we stand with respect to dynamical climate prediction?

- Statistical and hybrid techniques can provide a benchmark for dynamical approaches
- The main challenge to dynamical methods is a rigorous skill assessment.
  - » For this, consistent regional climatologies need to be constructed